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Why Phenology Matters: Unlocking Stage-Dependent Remote Sensing Signals to Improve Corn Yield Prediction Across the U.S. Corn Belt

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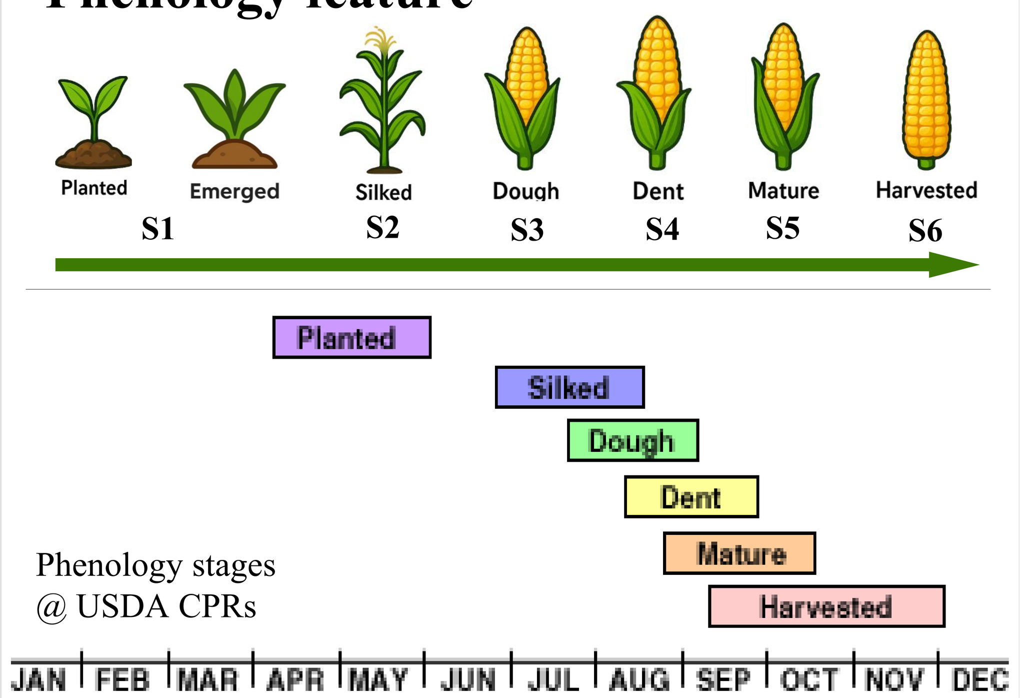
SCAN ME

INTRODUCTION

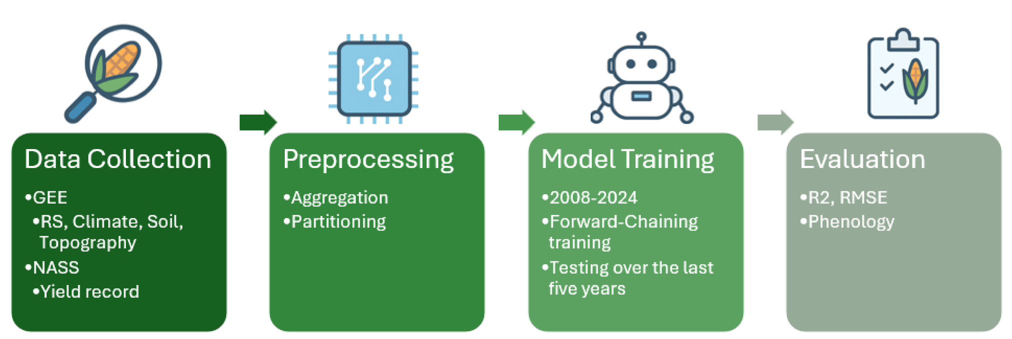
- **Significance**: food security under climate stress
- **Task**: county-level corn yield prediction
- **Challenge**: spatiotemporal complexity
- **Method**: phenology-guided patch-based deep learning network

Phenology feature



- Physiological development stages of crop growth from planting to harvest
- Six stages: S1-S6

WORKFLOW

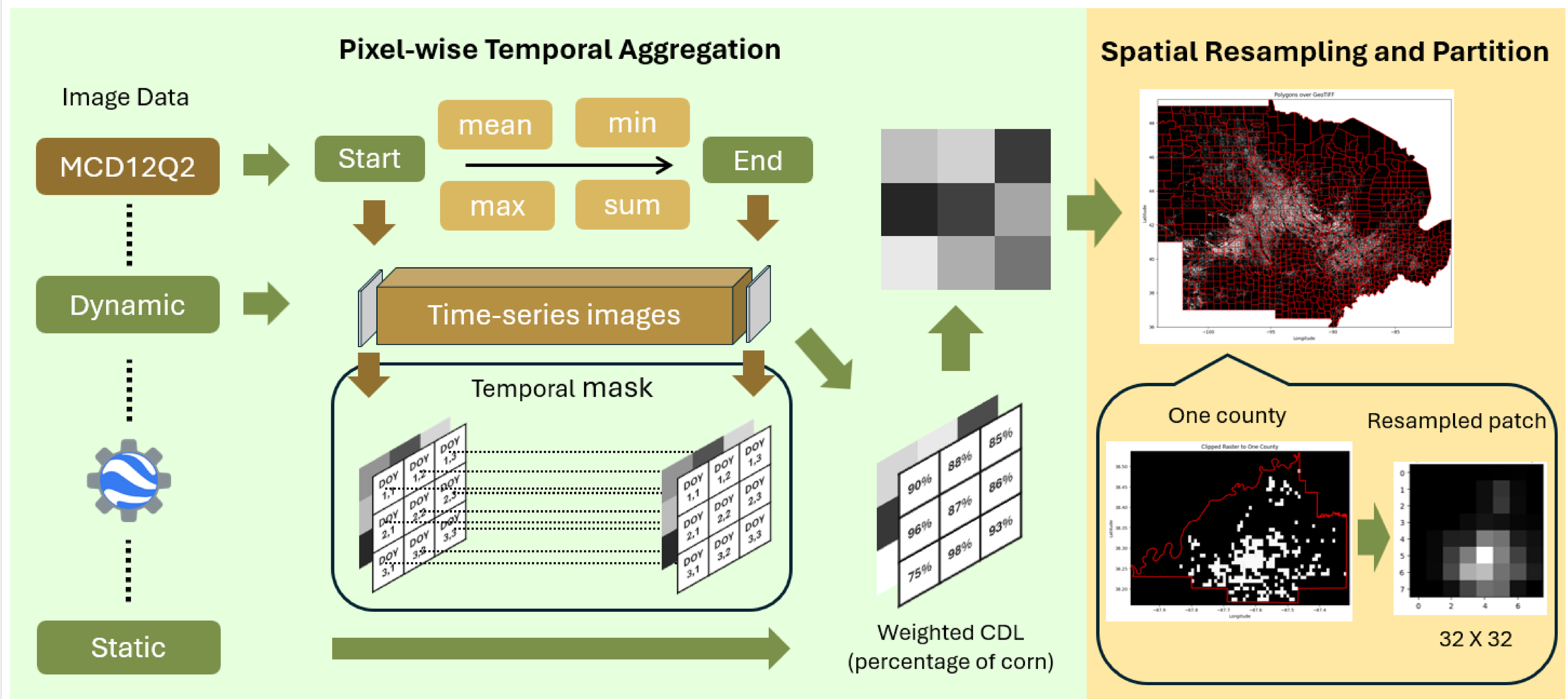


Study Area: U.S. Cornbelt Counties
Data Sources: GEE (MODIS, Daymet, PRISM, GLDAS, Open Land Map), USDA
Contributions:

- Phenology-guided feature engineering
- Phenology-empowered patch-based learning
- Dual-branch multimodal data fusion network with FiLM and cross-attention
- Roughly **30%** of performance boost by integrating phenology information

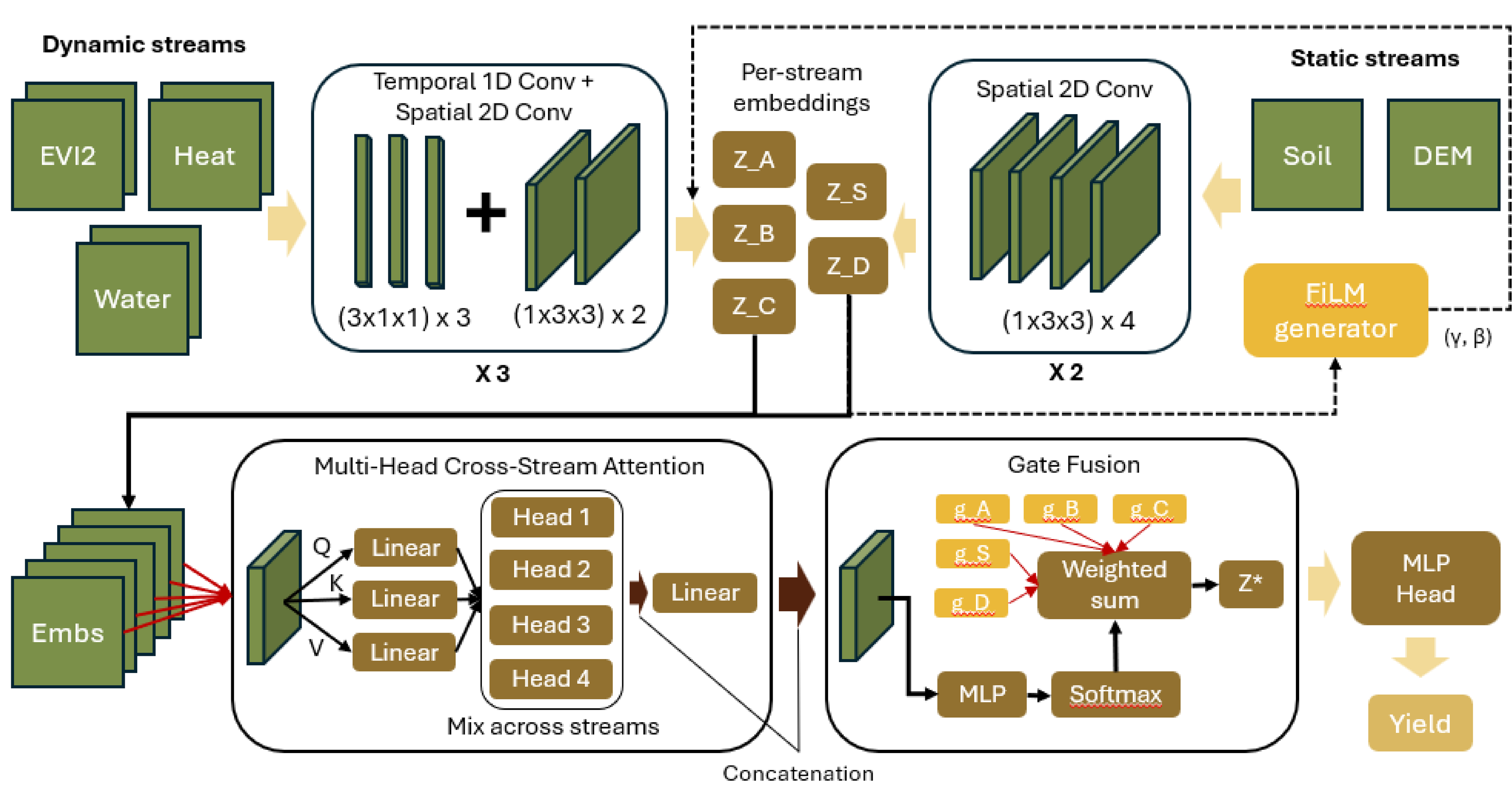
METHODOLOGY

Phenology-Guided Feature Engineering



- **Pixel-wise phenology aggregation**: group observations by phenology dates so the model aligns inputs by biological stages
- **Weighted Cropland Data Layer**: fractional mask, emphasizing areas with higher corn probability and reducing noise from mixed pixels
- **Spatial resampling and partition**: condense spatial information while retaining key biophysical signals, improving computational efficiency without losing important patterns

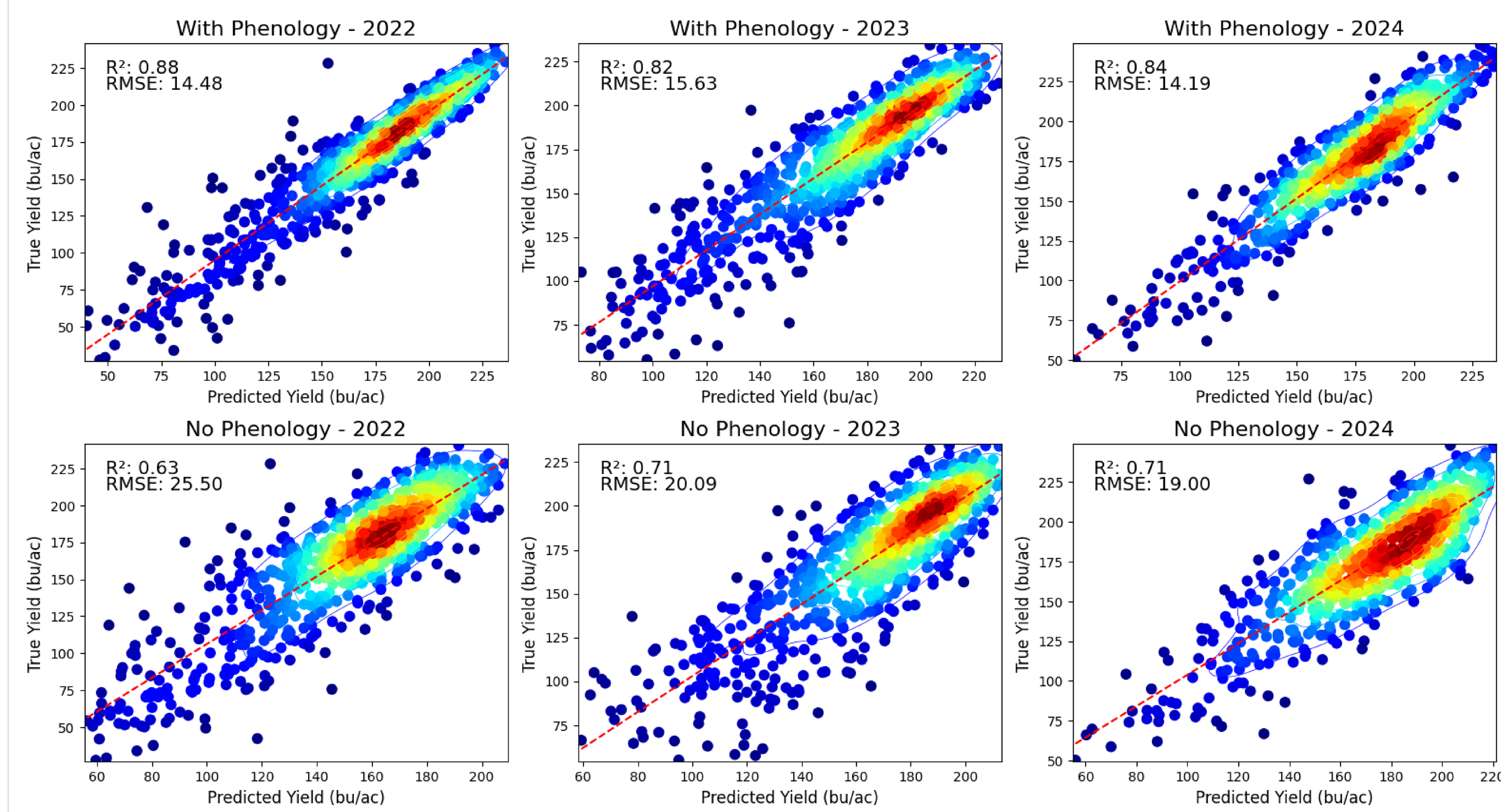
Dual-Branch Multimodal Fusion Network with Cross-Attention



- **Dual branch, multi-stream**: uses separate encoder branches for time-varying (dynamic) inputs and time-invariant (static) inputs
- **Cross-stream attention data fusion**: learn how information from different streams relates and contributes jointly
- **FiLM** (Feature-wise Linear Modulation): applied to static features so they adjust based on the current growth-stage signals

RESULT

Scatter Plot (with vs. without phenology)

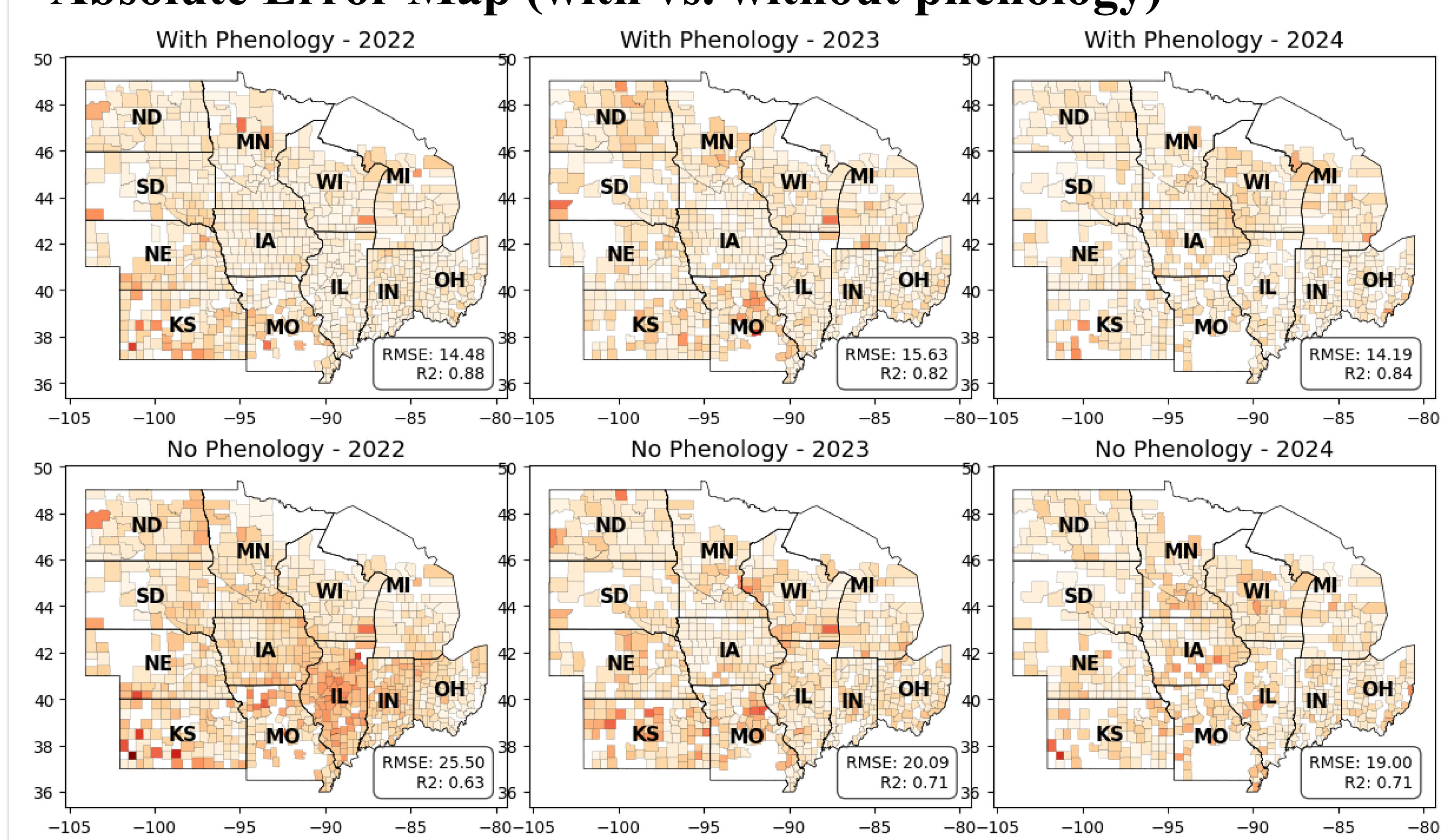


Key takeaways:

- Phenology significantly improves yield prediction.
- Reduced scatter and tighter clustering along the 1:1 line
- Better generalization across years
- Large improvements at low and high yield extremes

Summary:
Stage-aware information substantially improves both model robustness and predictive skill

Absolute Error Map (with vs. without phenology)

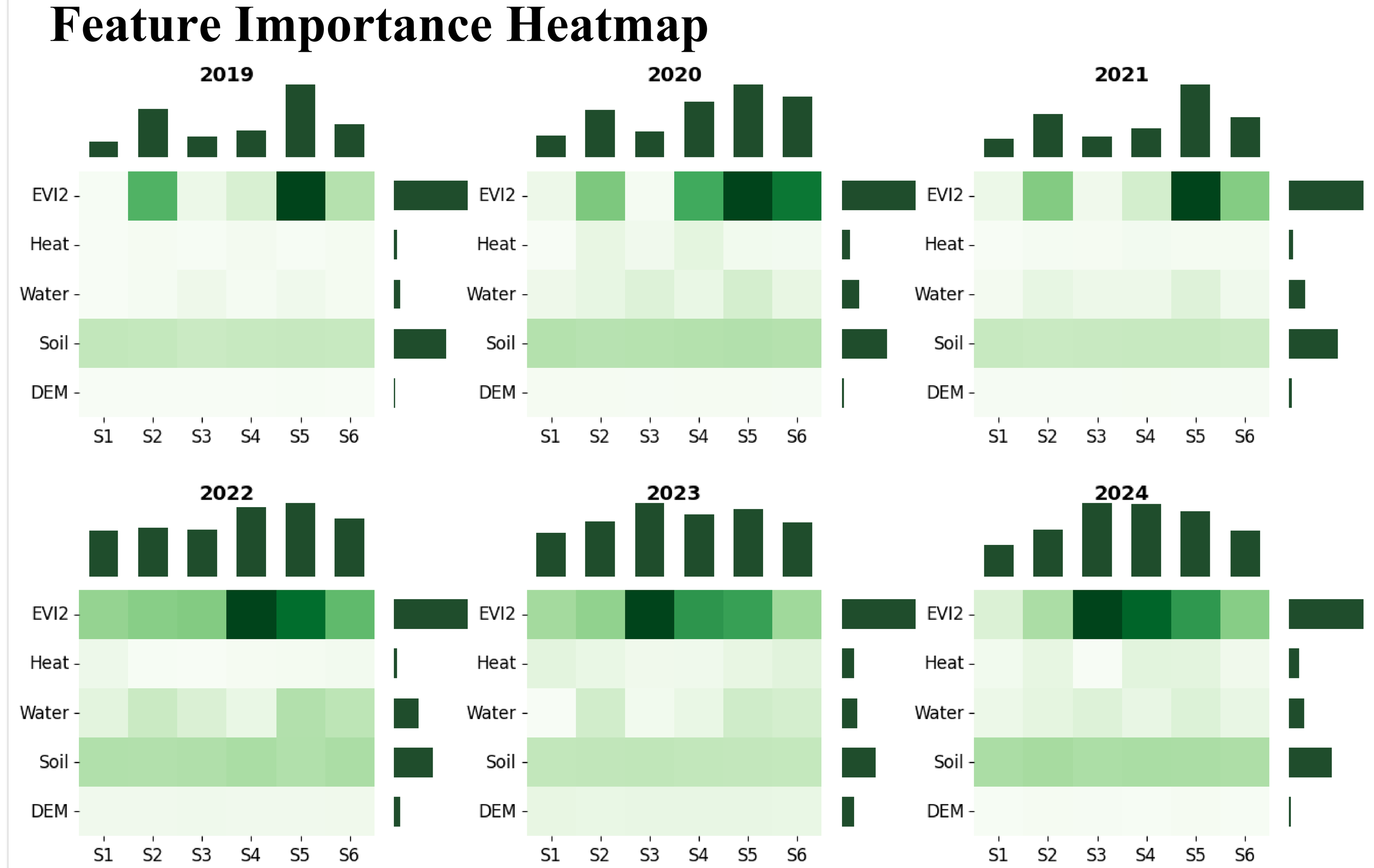


Key takeaways:

- Phenology sharply reduces spatial error
- Errors without phenology are larger and more clustered
- Spatial consistency improves year-to-year
- No-phenology models miss local stress signals

Summary:
Phenology information is crucial in improving spatial robustness

Feature Importance Heatmap



Key takeaways

- EVI2 dominates predictive importance
- Peak sensitivity consistently occurs at Stage 5
- Soil features maintain a stable, moderate baseline influence
- Interannual patterns remain highly consistent

Summary:
Across all years, the model consistently relies most on EVI2 during mid- to late-season stages